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Pacific Asia Conference on Information Systems (PACIS)

2015

Cross-Promotion in Social Media: Choosing the Right Allies

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CROSS-PROMOTION IN SOCIAL MEDIA: CHOOSING THE RIGHT ALLIES

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Abstract

This paper investigates the strategic use of cross-promotion for content producers in social media. In particular, we study how a producer chooses other producers to cross-promote so as to maximize the expected benefits of them cross-promoting him/her in return. Theories on homophily effect and social influence suggest that cross-promoted producers are more likely to cross-promote the initiator in return when they are in the similar categories or share more common friends and when the initiator has higher status. However, the cross-promotion from producers of different categories and social groups (i.e., share fewer common friends) tend to benefit the initiator more. The benefits also increase as the status of the initiator increases. We collected a panel of data consisting of 27,356 producers' profile and status information, content categories, and their cross-promotion activities over a period of two months from YouTube. To test our hypotheses, we first employ a cox proportional hazard model to estimate the probability of cross-promotion in return. Then, we use a difference-in-differences method with panel fixed effects to evaluate the effect of cross-promotion in return on the initiator. Our results strongly support our hypotheses and provide valuable insights for both content producers and social media platforms.

Keywords: homophily, social influence, cross-promotion, common friends, status

1 INTRODUCTION

"*Alone we can do so little; together we can do so much.*"

— Helen Keller

Over the past decade, social media has revolutionized the communication between businesses, organizations, communities, and individuals. It integrates the explosive growth of user-generated content (UGC) with the help of social networking functions provided by social media websites. With the social networking functions, users can not only discover and consume content of interest but also interact and even collaborate with other users. Such social links are effective in helping content producers to form an interconnected community. As millions of content producers must compete strategically for attention, being well-connected can be a producer's unique competitive advantage. By working with other producers through social connections, the generated cross-promotion and collaboration can be one of the most powerful ways to reach new audiences[1]. The cross-promotion from other producers, especially the well-established ones, can potentially direct the traffic for their content to their promoted producers' content. Most producers cross-promoting others expect to be cross-promoted in return to achieve mutually beneficial relationships. However, by and large, all producers are competing with each other for attention. As such, producers may decide not to cross-promote certain producers to avoid losing consumers, especially loyal followers, to cross-promoted producers. Therefore, the decision on cross-promotion can be complicated and also strategically important.

This study aims to investigate how to choose other producers to cross-promote their content so as to increase the expected benefits for one's own content. In the paper, we refer to the proactive producer who initiates the link as C producer and the reactive producer who receives the incoming link and then decides whether to link back as F producer. For producer C, the expected benefits of cross-promoting F are determined jointly by the probability of F cross-promoting C in return and the benefits of F's cross-promotion on C. Therefore, we attempt to answer two research questions: (1) among all the producers that a producer has cross-promoted, which are more likely to cross promote him/her in return? (2) Which can generate more benefits for him/her if being cross-promoted in return? We explore the answers for the questions from the perspectives of social influence and homophily. Using data from the largest video-sharing website YouTube on a large number of users' cross-promotion relationships and the consumption of their content over time, we find that among the cross-promoted producers, those with more similar content and more common friends are more likely to cross-promote the initiator in return, but more benefits for the initiator come from those with less similar content and less common friends. We also find that both the probability of the initiator being cross-promoted in return and the resulting benefits increase as the status of the initiator increases.

This research contributes to the literature in the following ways. First, we look at the cross-promotion as a way for users to collaborate for success in social media. Most studies on user generated content focus on incentives of user contribution and users' contribution behaviour (Butler 2001; Koh et al. 2007; Tang et al. 2012; Zeng & Wei 2013). Surprisingly little research has addressed the strategic collaboration among individual users. In the present study, we look beyond the individual behaviour of each user and examine the interaction between users. Second, this study examines the cross-promotion relationship between content producers as a unique type of social ties in online social networks. It is different from traditional friend relationship because of the competition between the two users. It is also different from the following or subscription relationship because in addition to being interested in the other user's content, the initiator is essentially recommending the content to his/her followers/subscribers. Third, we contribute to the literature on social influence and homophily by empirically testing our hypotheses derived based on the theories. We adapt the definitions for friends and similarities to fit our setting of cross-promotional network. Finally, using data on both users'

[1] http://www.reelseo.com/cross-promotion-youtube-video-collaborations/

content generation and social networking activities, the findings of this study will enrich our understanding of user behaviour in social media.

The rest of this paper is organized as follows. We present a literature review in Section 2. Section 3 describes our research context. Research hypotheses are introduced in Section 4. We then present the research data in Section 5. Section 6 presents empirical analysis and results. Finally, we discuss the findings and conclude with management implications in Section 7.

2 LITERATURE REVIEW

Prior studies on social links can be categorized into three topics according to the type of the link.

2.1 Social Links between Content Consumers

Social links between content consumers can facilitate the information exchange between the consumers. The relationship between two content consumers can be described by tie strength, which represents the closeness and interaction frequency between the two parties (Granovetter 1973). Strong social links exist between close friends who interact frequently and whose social circles overlap. In contrast, weak social links are social relationships with infrequent interactions, as commonly observed between acquaintances or strangers. Information from strong social links exhibits a stronger persuasive effect than that from weak social links and thus recommendations from strong social links are more likely to be adopted (Brown & Reingen 1987; Bapna & Umjarov 2015).This is because information from strong social links is believed to be more personalized and relevant as compared to that from weak social links (Anand & Shachar 2009; Krackhardt 1992). However, messages from weak social links can be more effective in increasing users' awareness of new information than those from strong social links (Van der Lans et al. 2010; De Bruyn & Lilien 2008; Godes & Mayzlin 2009). This is because weak social links often convey novel information or recommend products that are not easily discovered from one's close social circle (Shi et al. 2014).

2.2 Social Links between Content Consumers and Producers

Prior studies on social links between consumers and producers focuse on how the link between a consumer and a producer affect both the consumer's and the producer's behavior. These links are often observed as consumers following or subscribing to the producer. For producers, these links can increase the consumption of their content and the formation of new links between other consumers and the producer (Susarla et al. 2012; Sheldon et al. 2011; Shi et al. 2014). For consumers, they can express their viewpoints or interact with other consumers in brand communities such as fan pages on Facebook or official micro-blogs on Sina micro-blog, to affect producers' behaiors (Goes et al. 2014). Indeed, more than 1.5 million businesses have established brand communities for marketing purposes (Goh et al. 2013), which is consistent with the well-known Hawthorn Effect (Adair 1984), where the mere presence of observers can change behaviors.

2.3 Social Links between Content Producers

Existing empirical studies of social links between producers and producers in information systems have largely focused on how producers' behaviors (social links) are affected by social links (producers' behaviors) (Zeng & Wei 2013; Wang et al. 2015; Ma 2010) and the mechanism of such links (Stephen & Toubia 2010; Mayzlin & Yoganarasimhan 2012). On the one hand, social links can affect producers' behaviors. For example, rating and content similarity between producers are generally higher after the formation of social links (Zeng & Wei 2013; Wang et al. forthcoming). On the other hand, producers' behavior can also affect the formation of social links. Ma (2010) reveals that when producers produce higher volume of content, they are more likely to strategically initiate links and to "invite" reciprocation. Regarding the mechanism of this type of link, studies on the bidirectional links show that allowing online producers to link to one another can bring benefits to them because of the increased accessibility (Stephen & Toubia 2010; Jabr & Zheng 2014). More recently, studies begin to differentiate unidirectional links from bidirectional links, and find that although the producer may promote the rivals throuth these links, doing so improves the consumers' inference about its quality and ultimately increases the traffic to its own content (Mayzlin & Yoganarasimhan 2012; Katona & Sarvary 2008). Our study falls into this category by studying the formation of social links between content producers and the influence of such links.

3 RESEARCH CONTEXT

Established in February 2005, YouTube attracts more than 1 billion page views each month and over 100 hours of video are uploaded to YouTube every minute[2]. YouTube provide users with strong functionality to allow users to interact socially. Users can subscribe to others' uploaded content by subscribing to their channels. A user can unilaterally decide to subscribe to a producer, and the relationship does not have to be reciprocated. The subscribers would receive updated content from the subscribed channels but not the other way around.

In March 2013, YouTube launched a new channel design for YouTube producers called "Channel One"[3]. It enables "Featured Channels" function that allows producers to cross promote other producers, serving as a form of endorsement of the promoted producer by the source producer, and make the promoted producer's content easily accessible from the source (Figure 1). Ever since, many producers have cross promoted each other's content on YouTube. Many reports suggest that it is an efficient way to gain more subscribers and viewers through such collaboration[4]. The cross promotion relationship does not have to be reciprocated either. The featured channel relationship between two producers can be no links, one-way links, or mutual links.

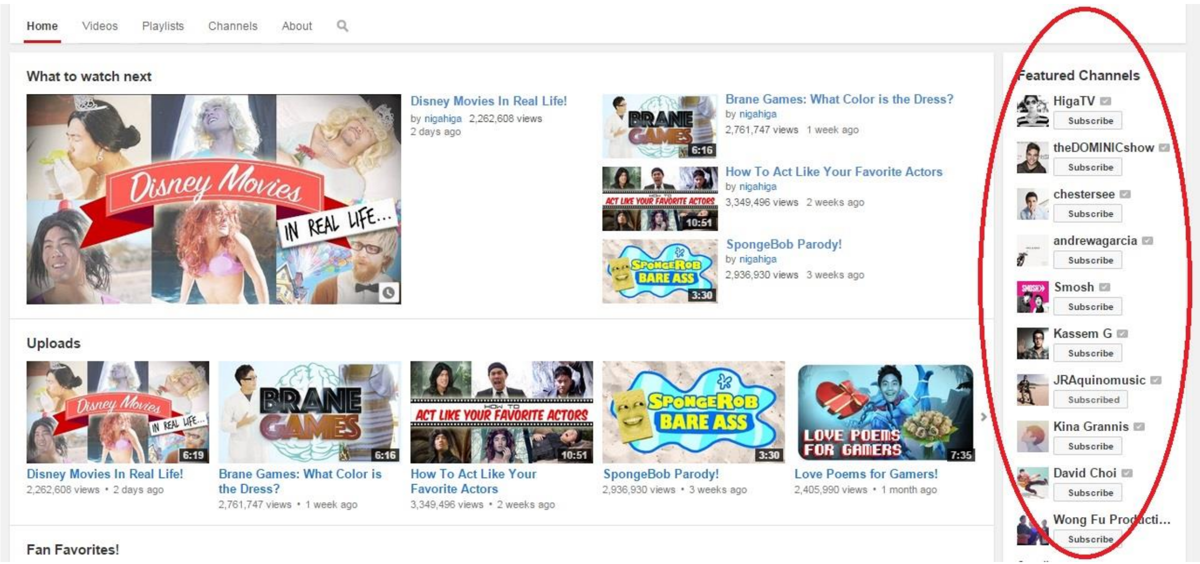

Figure 1. Featured Channels in one YouTube channel page.

Figure 2 shows both the subscription relationship between a consumer and a producer and the cross promotion relationship between two producers. In this study, we examine the formation of featured channel relationships and their influence on the formation of subscription relationships.

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[2] https://www.youtube.com/yt/press/statistics.html
[3] http://www.edelmandigital.com/2013/03/06/youtube-announces-channel-redesign
[4] https://blog.kissmetrics.com/2013-youtube-marketing-guide/

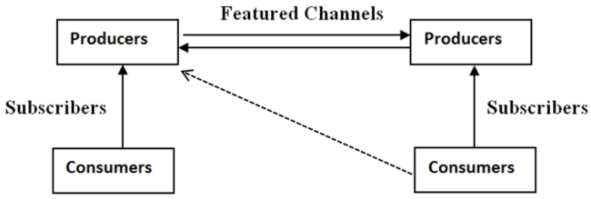


Figure 2. The subscription relationship between producers and consumers and the featured channel relationship between producers on YouTube.

4 RESEARCH HYPOTHESES

From hereafter, we refer to the proactive producer who initiates the cross-promotional link as C producer, and the reactive producer who receives the incoming link and then decides whether to link back to cross-promote C in return as F producer. As the link is directional, to achieve mutual cross-promotion between C and F, the first stage is C-to-F linking , and the second stage is F-to-C linking back. In this paper, we focus on the second stage and study the formation and impacts of F-to-C link given the existence of C-to-F link. The expected payoff from F-to-C link for C is determined joinly by the probability of F-to-C link formation and its influence after formation. In this section, we develope our research hypotheses regarding F-to-C link formation and influence drawing upon theories on social influence (Ma et al. 2015; Joseph et al. 2014; Aral & Walker 2014) and homophily (Zeng & Wei 2013; Ma et al. 2015).

4.1 F producers' Decision on the Formation of F-to-C links

The phenomenon of homophily contends that people with similar characteristics are likely to establish social links (McPherson et al. 2001). Similar characteristics can be intrinsic characteristics, or extrinsic interests, beliefs, and opinions (Zeng & Wei 2013). Homophily can play an important role in understanding human behavior in a network environment (Ma et al. 2015; Aral & Walker 2014). The mechanism underlying homophily is the selection effect (Easley &d Kleinberg 2010, p. 86), that is, people tend to select those with similar characteristics to form social ties. In our context, the similarity between F and C can be reflected in their content similarity and may affect F's decision of linking back to C. Because of homophily or selection effect, F is more likely to link back to C when F and C produce content in the similar categories. This leads to the following hypothesis:

H1: F producers are more likely to link back (cross-promote C in return) when C and F produce content in more similar categories.

Theories on social influence suggest that people's behaviors are affected by others (Ma et al. 2015). The influence can be either friends' active influence or general others' passive influence as one observes others' act (Ma et al. 2015; Sheldon et al. 2011; Shi et al. 2014; Zhang 2010). Information from friends is more influential because of the strong tie strength (Anand & Shachar 2009; Krackhardt 1992; Tam & Ho 2005). Hence, if two people share a friend in common, they are very likely to form social ties between themselves. Therefore, the likelihood of F producers' linking back to C would be affected by the common friends of C and F. The friends that two producers share in common make it easier for producers to trust each other, resulting in an increased likelihood that they will become friends themselves at some point in the future, as suggested by the principle of triadic closure (Easley & Kleinberg 2010, p. 48). More common friends also lead to greater cooperation because news of noncooperative behavior spreads quickly in the network, making it harder for the uncooperative actor to maintain friendly ties with others within the network. As such, common friends promote the development of cooperative norms that facilitate mutual helping relationships (Coleman 1988; Granovetter 1985). Both trust and cooperation are likely to increase the likelihood of linking back. This leads to the following hypothesis:

H2: F producers are more likely to link back (cross-promote C in return) when C and F have more common friends.

Meanwhile, researchers in economics and marketing have found that people tend to follow aggregated decisions of a population when selecting from a set of alternatives (Banerjee 1992; Bikhchandani et al. 1998; Zhang 2010). Generally speaking, people are more likely to form social links with popular others. As such, the standing of producer C among all producers is likely to affect the probability of producer F linking back to C. First of all, the high social status of C producer, usually represented by a large number of followers for her/her content, creates the perception that C's content is of high quality and leads F to believe that C's content is valuable for F's followers. Second, high status C producers can further increase F producers' chances of attracting content consumers by better improving the page ranks of F producers. According to the algorithm of eigenvector centrality used by many search engines, connections to high status producers contribute more to the centrality score of a producer (Zhang et al. 2007; Agichtein et al. 2008; Dellarocas et al. 2012; Brynjolfsson & Smith 2000; Stephen & Toubia 2010). Hence, we propose the following hypothesis:

H3: F producers are more likely to link back (cross-promote C in return) when C has higher status.

4.2 The influence of F-to-C links on C producers

F-to-C links are incoming links for C producers and serve as endorsement from F to C for F's consumers and followers. First, search engines amplify the awareness effect of F-to-C links on C producer, because the increase of incoming links can improve the rank of a webpage under PageRank (Brin & Page 1988), making C's content more discoverable for general consumers. More importantly, the link directly makes C producer's content easily accessible for F's followers (Stephen & Toubia 2010). Therefore, being cross-promoted by other producers is generally considered to be beneficial for a producer. This leads to the following hypothesis:

H4: The F-to-C links as cross-promotion for C would lead to more followers for C producers.

Although the F-to-C links are generally beneficial for C's status, the actual benefits depend on how many new consumers F can bring and how much they would value C's content. In other words, the more F's consumers would follow C, the more benefits F-to-C links can generate for C. The value of C's content for F's consumers depend not only on its intrinsic quality, but also on the novelty of its content (Shi et al. 2014). In particular, Information from diverse groups allows people to receive heterogeneous and novel information (Constant et al. 1996; Granovetter 1983; Hansen 1999; Levin & Cross 2004; Weenig & Midden 1991). In our context, when C and F produce content in similar categories, C's content is less novel for F's followers. It is often the contents transmitted via less similar groups that result in a greater increase in the number of newly informed users (Godes & Mayzlin 2009; Granovetter 1973; Shi et al. 2014). Therefore, C producers tend to attract more consumers or subscribers from F, when C can provide novel and valuable information that is not easily discovered from F. Accordingly, we hypothesize the following:

H5: The less similar C and F's content are, the more F-to-C links would increase C's followers.

Similarly, if C and F share more common friends, they tend to be clustered into small groups (Cialdini & Sagarin 2005; Kruglanski & Mayseless 1990; Kardes 2002). Despite the fact that the presence of common links increases the level of trust (Granovetter 1985; Uzzi 1996), it also increases the level of redundancy of content. However, higher levels of knowledge redundancy are less likely to provide access to novel information (Hansen 1999). Therefore, we propose the following hypothesis:

H6: The fewer common friends C and F have, the more F-to-C links would increase C's followers.

Prior studies have shown that not all firms in the network benefit equally, resulting in firms aggressively bidding to secure the top positions (Ghose & Yang 2009). Where a producer is positioned in the network significantly influences the viewership of his/her content (Brin & Page 1998; Dellarocas et al. 2012). Indeed, status or popularity can be self-reinforcing, that is, higher status can help people earn significantly greater profit (Brynjolfsson & Smith 2000; Stephen & Toubia 2010). As such, the benefits that people gain may depend on their structural importance within a network. As previously mentioned, followers' valuation of the producers' content may depend on its intrinsic quality. However, when limited information on producers' quality is available, potential followers often observe the actions of others and extract information about the value of actions from others' choices (Zhang 2010; Bikhchandani et al. 1998; Cai et al. 2009; Chen et al. 2011). Therefore, high status C producers may attract more consumers as their status tends to be self-reinforcing (Chen et al. 2011; Salganik et al. 2006; Zhang 2010). Hence, we hypothesize the following:

H7: The higher status C holds, the more F-to-C links would increase C's followers.

5 DATA

We collected a panel of data consisting of producers' profile and status, featured channels, and video categories over a period of two months, from May 10 to July 8, 2014 from YouTube. Producers were sampled in a snowball fashion. We started from a random producer as a seed and added the producer's featured channels into the sample set. We then kept searching for featured channels of all the producers in the sample list and added their featured channels into the list, and so on. We stopped searching for new sample producers at 7 degrees from the seed producer[5]. Our dataset contained complete linking information of all producers in the first 6 degrees. The existence of the 7th degree was to ensure that the sub-network was closed. Our analyses were based on the sample of the first 6 degrees. From day two and onwards, the list of sample producers were re-examined, and if producers in the first 6 degrees had added any featured channels not in the sample, then those new featured channels were added to the sample as well as all the featured channels reachable from the new producers.

Based on daily changes of producers in our sample, we recorded producers' daily linking information. That is, we recorded the changes of each producer's links and the time when linking changes took place (e.g., from one-way link to mutual links). In this way, we were able to observe the benefits of producers in the dyad in different phases of linking formation, which allowed us to adopt a within-subjects design. We retrieved daily information of producers in the sample, including producers' number of views, number of subscribers, number of comments, number of videos, number of featured channels, their age and whether producers allow YouTube to recommend related channels in their channel pages. Also, we collected category information of producers' all uploaded videos till the end of the collection period.

Variable	**Statistics**
Data collection duration	60 days
Number of producers on day one	27,356
Number of featured channels by day one	153,182
Average number of featured channels per producer by day one	5.6
Average number of featured channels established per day	240
Number of video uploads	215,221

Table 1. Network Characteristics in Our Sample

On day 1, our sample contained 27,356 producers, which distributed in the 16 categories of YouTube. On average, a producer had 5.6 featured channels, but the distribution was uneven: 22.14% of

[5] Given the time consuming and the restriction of YouTube API, we can scrawl limited information per day. To guarantee complete producer information, producers' link information and video information, we just scrawl 7 degrees. Producers in the 7th degree do not contain complete link information. The seed producer is treated as the 0th degree.

producers had no featured channels, about 75% of producers had less than 20 featured channels, and less than 3% of producers had more than 20 featured channels. Among those producers, about 33% of them had not mutual links, while others had 1 to 60 mutual links. At the end of the period, our sample size increased by 6.7%, the number of featured channels increased by 9.4%, with a daily increase of 240 featured channels and only 19.64% of producers had no featured channels. During the 60-day period, our sample generated 215,221 videos altogether. On average, each producer uploaded 7 videos during this period, with the maximum 1605 videos. Table 1 summarizes the sample's statistics.

6 ANALYSIS AND RESULTS

6.1 Measures and Variables

In this section, we first define three important measures for our hypothesis testing: content similarity, common friends, and producer status and then describe key variables. As YouTube only defines 18 categories for videos but not for producers, many producers post videos in multiple categories. As such, the category for a producer can be described as a vector:

$$category_{it} = [category_{it1}, category_{it2}, \cdots\cdots, category_{itk}, \ldots\ldots category_{it18}],$$

where $category_{it}$ is the category of producer i at time t, $\text{category}_{\text{itk}}$ is the percentage of producer i's content in k^{th} (k=1,2,...,18) YouTube video category among all i's content. We can then use cosine similarity to calculate the similarity of two producers in terms of their content (Manning et al. 2009; Zeng & Wei 2013) as follows:

$$categorySimilarity_{ijt} = \frac{\sum_{k=1}^{18}(category_{itk} * category_{jtk})}{\sqrt{\sum_{k=1}^{18}(category_{itk})^2 \sum_{k=1}^{18}(category_{jtk})^2}}$$

According to social tie theories (Easley & Kleinberg 2010), the role of common friends is (1) to increase the opportunity for two people to meet and (2) to give them a basis for trusting each other. As the cross-promotion relationship is directional and much weaker than traditional friend relationship, the common featured channels in the cross-promotion relationship shown in Figure 3(a) only represent the common interest of C and F in another producer A and are unlikely to increase the chance for F to discover C or establish basis for F to trust C. Therefore, we restrict common friends for our context to be those common featured channels that also feature C as in Figure 3(b). As the common friend A is featuring C and is featured by F, it is more likely for F to discover C among A's featured channels. Meanwhile, as F trust A's content, A trust C's content, it is more likely for F to trust C's content. Thus the modified definition can satisfy the two requirements for common friends. Given this definition,

$$commonFriends = Num(\,mutual\ links\ of\ C\ |common\ featured\ channels\ shared\ by\ C\ and\ F)$$

(a) Common interest (b) Common friend

Figure 3. Definition of common interest (a) and common friend (b).

The popularity of a YouTube producer can be described with either video views or subscribers. Unlike viewers, subscribers represent loyal viewers who are willing to receive notifications of the producer's new videos and are more likely to view these new videos in the future. So we use number of subscribers to measure the status of a producer. As the distribution of number of subscribers among YouTube producers are highly skewed, we take the log transforamtion of subscribers ("+1" is used to maintain the observations with no subscribers). In particular, the status of a producer i is calculated as:

$$LogSub_{it} = log(Subscribers_{it} + 1)$$

The main variables and their descriptions are shown in table 2, where i and j are index for producers and t is the index for time.

Variables	Descriptions
$LogSub_{ijt}$	$LogSub_{ijt} = LogSub_{it}$
T_CF_{ijt}	$T\_CF_{ijt} = \begin{cases} 1, & producer\ i\ is\ featuring\ j\ at\ time\ t; \\ 0, & otherwise. \end{cases}$
T_FC_{ijt}	$T\_FC_{ijt} = \begin{cases} 1, & producer\ j\ is\ featuring\ i\ in\ retrun\ at\ time\ t; \\ 0, & otherwise. \end{cases}$
$LogSub_{i0}$	Status of producer i when j features i back or when i features j if j does not feature back i during the data period.
$categorySimilarity_{ij}$	Content similarity of i and j
$commonFriends_{ij}$	Common friends of i and j
$weekend_t$	Equals to 1 if day t is weekend and 0 otherwise.
X_{ijt}	Vector of control variables for producer i's characteristics including log number of views, log number of comments, log number of videos, number of channels featuring i (in-degree), number of featured channels (out-degree), number of mutual links, time since producer i registered with YouTube , whether i allows YouTube to recommend related channels on i's channel pages, log sum of in-degree channels' views, log sum of in-degree channels' subscribers, log sum of in-degree channels' comments, log sum of in-degree channels' videos, log sum of out-degree channels' views, log sum of out-degree channels' subscribers, log sum of out-degree channels' comments, and log sum of out-degree channels' videos.

Table 2. Variables and Descriptions.

6.2 Model Specification

6.2.1 F producers' Decision on the Formation of F-to-C links

We use Cox proportional hazards model to estimate the effect of homophily and social influence on the probability of a cross-promoted producer cross-promoting back (Aral & Walker 2011, 2012; Iyengar et al. 2011; Nam et al. 2010; Van den Bulte & Lilien 2001). The model below simultaneously estimates the impacts of content similarity, common friends, and status, while controlling for other producer characteristics and weekend effects.

$$\lambda(i,j,t) = \lambda_0(t) * exp(\beta_0 + \beta_1\, categorySimilarity_{ijt} + \beta_2 commonFriends_{ijt} + \beta_3 LogSub_{it} + \beta_i X_{ijt} + \beta_j X_{jit} + \beta_w Weekend_t + \varepsilon_{ijt}) \quad (1),$$

where $\lambda(i,j,t)$ is the rate of producer j featuring back producer i in return, $\lambda_0(t)$ is the baseline rate of featuring back. We are most interested in three coefficients: β_1 , β_2, and β_3,representing the percentage increase or decrease in the featuring back rate associated with the increase in content similarity, common friends, and $\mathrm{i}'\mathrm{s}$ status respectively. Coefficients greater than 0 represent an increase in the rate of featuring back; coefficient less than 0 represent a decrease. Based on hypotheses H1, H2, and H3, we expect β_1 , β_2, and β_3 to be all positive.

6.2.2 The Effect of F-to-C links on C producers

To assess the effect of F-to-C links on C producers, we employ a difference in differences (DID) method. In our context, the treatment is F featuring back C, the treated group is therefore the producers with other producers featuring back during the period, and the control group is the producers without any producers featuring back during the period. The treatement effect is identified by comparing the treated group before and after the treatment with the control group before and after the treatment. The subject is analysized at the two-producer pair level. Some producers in our sample initiated multiple cross-promotion relationships with other producers and received multiple cross-promoted producers cross promoting them in return. For these samples, we partition the 60-day period into several parts to reflect different producer pair observations. As shown in Figure 3, producer C initiates cross-promotions for two producers: F_1 at time T_0 and F_2 at time T_2, while F_1 started to cross promote C at T_1 and F_2 at time T_3. In the estimation, we use the period from the beginning to T_2 as the observation for C-F_1 pair and the period from T_1 onwards as the observation for C-F_2 pair.

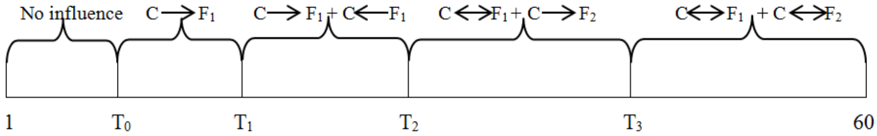


Figure 3. Partition of time for producers with multiple cross-promotions from cross-promoted producers.

The baseline DID model,

$$LogSub_{ijt} = \gamma_0 + \gamma_1 T\_CF_{ijt} + \gamma_2 T\_FC_{ijt} + \gamma_i X_{ijt} + \gamma_j X_{jit} + \gamma_\omega weekend_t + \mu_{ij} + \alpha_t + \epsilon_{ijt} \qquad (2)$$

estimates the influence of producer j featuring back producer i on i's status, where T_CF_{ijt} is the indicator for whether i is featuring j at time t, T_FC_{ijt} is the indicator for whether j is featuring i in return at time t, Y_{ijt} and Y_{jit} are used to control for producer i and j characteristics respectively, $weekend_t$ is the indicator for weekend, μ_{ij} is the producer pair specific effect, α_t is the time specific effect, and ϵ_{ijt} is the error term. To further examine how the influence of featuring back varies as content similarity, common friends, and producer status, we extend model (2) to include the interaction of the treatment indicator and the factor of interest as follows:

$$LogSub_{ijt} = \gamma_0 + \gamma_1 T\_CF_{ijt} + \gamma_2 T\_FC_{ijt} + \gamma_3 T\_FC_{ijt} * categorySimilarity_{ij} + \gamma_i X_{ijt} + \gamma_j X_{jit} + \gamma_\omega weekend_t + \mu_{ij} + \alpha_t + \epsilon_{ijt}, \qquad (3)$$

$$LogSub_{ijt} = \gamma_0 + \gamma_1 T\_CF_{ijt} + \gamma_2 T\_FC_{ijt} + \gamma_4 T\_FC_{ijt} * commonFriends_{ij} + \gamma_i X_{ijt} + \gamma_j X_{jit} + \gamma_\omega weekend_t + \mu_{ij} + \alpha_t + \epsilon_{ijt}, \qquad (4)$$

$$LogSub_{ijt} = \gamma_0 + \gamma_1 T\_CF_{ijt} + \gamma_2 T\_FC_{ijt} + \gamma_5 T\_FC_{ijt} * LogSub_i + \gamma_i X_{ijt} + \gamma_j X_{jit} + \gamma_\omega weekend_t + \mu_{ij} + \alpha_t + \epsilon_{ijt}, \qquad (5)$$

We are interested in coeffecients $\gamma_2, \gamma_3, \gamma_4$, and γ_5. Based on Hypotheses H4, H5, H6, and H7, we expect γ_2 and γ_5 to be positive and γ_3 and γ_4 to be negative.

6.3 Results

6.3.1 F producers' Decision on the Formation of F-to-C links

Table 3 presents the results of Cox proportional hazards model (1) on F producers' decision on the formation of F-to-C links. The coefficient of $categorySimilarity$ is significantly positive, suggesting that F producers are more likely to form F-to-C links when C and F produce content in similar categories than in different categories, supporting H1. The coefficient of $commonFirends$ is positively significant, indicating that F producers are more likely to link back when C and F share more common friends. Therefore, H2 is supported. The coefficient of $LogSub_i$ is also positive, statistically significant when not controlling for producer characteristics, but not significant after controlling for covariates. Thus H3 is not supported.

VARIABLES	Hazard Ratio (SE)				
	(1)	(2)	(3)	(4)	Model 1
categorySimilarity	0.272**	0.232*			0.288**
	(0.130)	(0.132)			(0.132)
commonFriends	0.849***		0.608***		0.598***
	(0.0786)		(0.0902)		(0.0948)

$LogSub_i$	0.0991***			0.0289	0.0153
	(0.0210)			(0.0382)	(0.0418)
Control Variables	NO	YES	YES	YES	YES
Observations	4,373	4,204	4,519	4,519	4,204

Table 3. F producers' decision on the formation of F-to-C links.

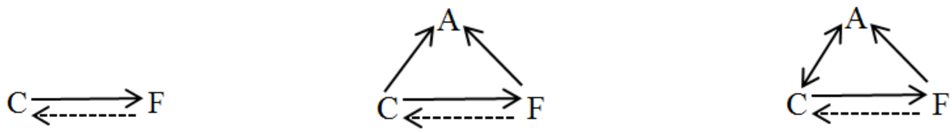
6.3.2 The influence of F-to-C links on C producers

Table 4 reports the main estimation results of DID analysis of the influence of F-to-C links on C producers. Generally, the coefficient of T_FC is positive and significant, suggesting that the linking-back act has a positive and significant effect on C's number of subscribers. Therefore, H4 is supported. The coefficient of T_CF, however, is negative and significant, indicating the formation of C-to-F links without F-to-C links in return is detrimental for C. Column (3) shows the main specification for model (2), with relationship-level fixed effects. It shows that the coefficient of T_FC is positive and significant, suggesting that the formation of F-to-C links increase C's subscribers. Hence, H4 is supported. The coefficients of $T\_FC * categorySimilarity$ is significantly negative, indicating F-to-C links increase C's subscribers more when C and F produce content in different categories than in similar categories. Hence, H5 is supported. Column (6) shows that C's status positively moderates the treatment effect of linking back on C, supporting H7.

	$LogSub_{ijt}$					
VARIABLES	(1)	(2)	(3) Model 2	(4) Model 3	(5) Model 4	(6) Model 5
T_FC			0.0493***	0.101***	0.0343***	-0.182***
			(0.00464)	(0.00781)	(0.00490)	(0.0156)
T_FC* categorySimilarity				-0.0856***		
				(0.00967)		
T_FC* commonFriends					0.0625***	
					(0.00656)	
T_FC* $LogSub_i$						0.0230***
						(0.00148)
T_CF	-0.238***	-0.106***	-0.0465***	-0.0454***	-0.0463***	-0.0486***
	(0.00785)	(0.00712)	(0.00281)	(0.00278)	(0.00281)	(0.00281)
feature_back	0.206***	0.109***				
	(0.00942)	(0.00842)				
Constant	0.338***	0.597***	3.985***	3.429***	3.999***	3.867***
	(0.0536)	(0.0538)	(0.416)	(0.443)	(0.416)	(0.415)
Control variables	YES	YES	YES	YES	YES	YES
Category Fixed Effects	NO	YES	NO	NO	NO	NO
Relationship Fixed effects	NO	NO	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES	YES
Observations	154,271	150,135	154,271	147,923	154,240	154,271
R-squared	0.776	0.819	0.066	0.077	0.067	0.068
Number of R_id				3,885	3,711	3,882

Table 4. The Effect of F-to-C links on C producers.

According to Column (5), the coefficient of $T\_FC * commonFriends$ is significantly positive, which is against H6. According to our definition of common friends, the results may be because either the existence of common friends or C's and F's shared interest in these common featured channels. We further make an additional analysis to disentangle the effects by dividing the data sets into three parts (Figure 5). Part (a) contains producer pairs without common interests or common friends, part (b) contains the pairs with only common interest but no common friends, and part (c) are the pairs with common friends. Comparing (a) with (b) can identify the moderating effects of common interest, while comparing (b) with (c) identifies the moderating effects of common friends. The results are shown in Table 5. The coefficients of *T_FC* are sigificantly positive in all groups. Compared to group (a), the effect of linking back in group (b) is significantly larger when C and F share common interests. However, compared to group (b), the effect of linking back in group (c) is significantly smaller than that in group (b), suggesting when common interest is present, the existence of common friends would reduce the benefits of F-to-C links. Therefore, H6 is also supported. The positive coefficient on *T_FC* commonFriends* in Table 4 is mainly driven by common interest instead of common friends.



(a) Placebo condition (b) Common interest (c) Common friend

Figure 5. Three parts of datasets.

	$LogSub_{ijt}$		
VARIABLES	Placebo condition	Common interests	Common friend
T_FC	0.0325***	0.0746***	0.0387***
	(0.00471)	(0.0257)	(0.00777)
T_CF	0.000189	-0.321***	-0.0537***
	(0.00279)	(0.0137)	(0.00527)
Control Variables	YES	YES	YES
Relationship Fixed effects	YES	YES	YES
Time fixed effects	YES	YES	YES
Observations	111,226	20,631	22,414
R-squared	0.072	0.083	0.300
Number of R_id	2,861	500	534

Table 5. Additional analysis of common friends' effects on link influence.

7 DISCUSSION AND CONCLUSION

In this research, we examine the social relations of content producers and the influence on their status in social media. In particular, we focus on the formation of cross-promotion relationships between producers and how such cross-promotions bring benefits for the promoted producers. Establishing links with other channels helps reach and attract new audiences. However, as each producer seeks to maximize the viewership of its own content, to attract viewership, producers need to find the right allies to effectively collaborate with. In this research, we explore which cross-promoted producers are more likely to cross-promote the initiator in return and the cross-promotions from which producers in return can generate more benefits for the initiator. Drawing on the existing literature on social links and theory on homophily and social influence, we observe a more nuanced relationship between the formation of cross-promotion and its benefits.

We find that the cross-promoted producers are more likely to cross-promote the initiator in return when they produce content in similar categories and when they share more common friends. More importantly, the results show that the formation of F-to-C links is generally beneficial for C producers. Besides, if C and F produce content in different categories, the F-to-C links increase C's subscribers more as C's content is informational for F's followers. By a detailed analysis, we find that the F-to-C links increase C's subscribers more when C and F share fewer common friends as the overlap of channels may increase the influence of one another, resulting in the content redundancy. In spite of the fact that F's linking back decision is not affected by C's status, C producers are more likely to gain more followers from the formation of F-to-C links when their own status is higher.

7.1 Contributions and Implications

Literature on social links has mainly examined the effect of links between consumers (Brown & Reingen 1987; Bapna & Umjarov 2015; Anand & Shachar 2009; Krackhardt 1992; Van der Lans et al. 2010; De Bruyn & Lilien 2008; Godes & Mayzlin, 2009; Shi et al. 2014). Depite the recent evidence of social links between producers, many studies have focused on the mechanisms of such links (Stephen & Toubia 2010; Mayzlin & Yoganarasimhan 2012). Our study contributes to the literature by investigating both the formation of social links and the influence of social links. The results has shown that although producers are more likely to establish links with similar others (i.e., with common friends and produce similar content), similar others are not necessarily an effective choice in increasing their number of subscribers. By examining the relative benefits of proactive producers, we have proposed that F-to-C links have a positive effect on C when C and F produce content in different categories and when they share fewer common friends.

Our study has great managerial implications for both content producers and social media platforms. Cross-promotion and collaboration with beneficial content producers in social media can be a strategic advantage for producers to competete with millions of other producers. For producers, since it is evident that producers may gain more benefits from incoming links than from outgoing links (Ma 2010), C producers expect that F can link back when they initiate links with F. Hence, it is important for producers to target the right producers to establish beneficial links. That is, producers should consider not only the possibility of linking back, but also the gained benefits after linking back. Based on our findings, although producers tend to link back when they are similar in content category as well as in social groups (i.e., common friends), it is the producers who produce content in different categories and who share few common friends that bring more subscribers to F. Producers hence should deploy reasonable strategies to initiate links, such as for low-status producers, since it is more important for them to gain more awareness from the public, they should initiate links with those who are more likely to link back as linking-back generally is beneficial; while for high-status producers, they should consider the linking strategies from a long run and select the producers whose linking back may bring them considerable benefits. For platform designers, the introduction of "featured channels" function is generally beneficial for YouTube itself because it increase the viewership as well as the subscription. However, the current utilization of this function may not be optimized by producers. The platform can recommend other producers for a producer to cross-promote based on the expected payoffs from each potential producer and promote the competitive collaboration among producers in social media.

7.2 Limitations and Future Extensions

This research also has a few limitations that may be addressed in the future. First, this paper only considers the measure of category similarity. However, we do not consider the fact that some categories represent closer semantic groups than others (Cattuto et al. 2008; Zeng & Wei 2013). For example, the "comedy" category is more related to the "Entertainment" category than to the "Nonprofits and Activism" category. In the future, we may consider group the more similar categories into one new category. Second, it is noteworthy that he snowball sampling captures all the outgoing links from producers in the sample but not necessarily all the incoming ones. This limitation is typical in studies that crawls directed graphs online (Cha et al. 2009). Future studies may try to obtain the complete data of the sub-network. Overall, our work is an early step towards social links among producers, and we are confident that future research will bring further insights in this area and offer much needed managerial guidance.

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